

A Review of GLCM, SVM, and MSVM for Early Disease Diagnosis in Sustainable Cotton Farming

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Keywords:

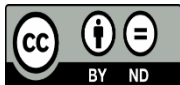
Cotton crop diseases, texture analysis, grey-level co-occurrence matrix (GLCM), support vector machine (SVM), multi-class support vector machine (MSVM), machine learning, image processing, disease detection.

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ABSTRACT

This research paper takes a close look at how the grey-level co-occurrence matrix (GLCM), support vector machine (SVM), and multi-class support vector machine (MSVM) methods for texture analysis can be used to find diseases that affect cotton crops. In the field of agriculture, Cotton is vital as the world economy mostly depends on it. Still, the sensitivity of the cotton crop to several diseases seriously jeopardizes productivity and quality. Integration of sophisticated image processing and machine learning techniques has become a potential answer for early and accurate disease identification to handle this problem. The first part of this review emphasizes the need for cotton crops in agriculture and the need for strong disease-detecting techniques. A comprehensive examination of the GLCM approach is presented, focusing on its ability to extract textural features from images. The SVM method is then evaluated for its relevance to disease detection in cotton crops and its efficacy in classification tasks. This paper also discusses the MSVM, a sophisticated variation of the SVM that enables concurrent classification of many categories. Comparative studies are undertaken to assess the advantages and disadvantages of GLCM, SVM, and MSVM for disease detection in cotton crops. The review of significant studies and implementations facilitates comprehension of the beneficial outcomes of these strategies. Moreover, challenges and potential areas for improvement in current methodologies are discussed, setting the stage for future research directions. The overarching objective of this review is to offer a consolidated understanding of state-of-the-art techniques for detecting diseases in cotton crops and to guide researchers, practitioners, and policymakers in implementing effective and scalable solutions for sustainable cotton cultivation.



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1. Introduction

India is rather well-known in the world cotton market, which greatly influences the dynamics of the textile

sector. Deeply ingrained in India's agricultural system, cotton is a fundamental basis for the livelihoods of millions of farmers all around. A key factor in India's industrial scene, the textile sector's strength is closely related to the success of the cotton sector [1]. Apart from its commercial worth, cotton is also a main source of income for Indian farmers, particularly in rural areas where farming shapes the basis of the local economy. For many, cotton farming is not only a source of revenue but also a way of life providing livelihoods and food that appeal to entire communities [1].

Despite its pivotal role, the sustainability of India's cotton production faces persistent challenges, primarily in the form of diseases affecting crops. From bacterial blight to wilt and boll rot, these diseases pose an ongoing threat to cotton yield and quality. The ramifications extend beyond individual farmers, impacting the overall agricultural economy and India's position in the global textile market [2].

A major participant in India's industrial sector, the textile sector mostly depends on consistent and high-quality raw cotton. Any disturbance in the cotton supply chain resulting from illnesses can have domino effects on textile manufacture, therefore affecting employment, exports, and economic development. The health and sustainability of cotton growing in India are vital not only for the agricultural sector but also for the broader economy [2]. Indian cotton sector survival requires balancing agricultural techniques, economic factors, and technological advances. Disease management is crucial and requires creative solutions. Advanced technologies like image processing and machine learning are being explored to make India's cotton sector more robust and sustainable [2].

Finally, considering cultural, social, and industrial aspects as well as its financial influence, the Importance of cotton farming in India exceeds. The difficulties caused by illnesses emphasize the need for aggressive and creative solutions to safeguard the livelihoods of millions of farmers and maintain India's central position in the world textile scene [2].

The significance of cotton crops in Indian agriculture is complicated in terms of economic, social, and cultural aspects that significantly define the agricultural scene of the country. These elements are thoroughly explored here.[3]:

- Through domestic consumption and export income, cotton farming notably affects India's GDP, so adding greatly to the country's total economic output [4].
- Small and marginal farmers depend mostly on cotton farming for their revenue; this shapes their financial situation and helps to reduce poverty in rural areas by means of cultural traditions [5].
- India's textile sector depends on premium cotton. Hence, both domestic and foreign demand is influenced. India is a big textile producer in the world, and its cotton exports help it earn foreign currency.
- Cotton's dual-use qualities provide fibre and seed, increase agricultural sustainability, interrupt disease cycles, improve soil health, and help farmers in mixed or diversified farming.
- India's government policies and actions demonstrate its major influence in the cotton market: they guarantee food and economic stability and help to define its posture in world trade negotiations [5].

Supporting rural livelihoods as well as the worldwide textile sector, the cotton crop is vital to Indian agriculture. Bacterial blight, wilt, and boll rot reduce crop yield and quality. Quick identification and management are essential for cotton farming's yield and profitability [5].

However, conventional illness detection relies on hand inspection and is subjective, laborious, environmental, and inaccurate due to experience and skill.

One major obstacle is the low scalability of human detection. Due to different farming methods, manually analyzing large cotton fields in India's costly environments is impossible. So, timely and reliable disease identification becomes difficult. Manual detection methods may delay disease outbreak reactions due to their volatility in early detection, affecting crop productivity and Cotton farmers' finances.

Figure 1 appears to be a diagnostic chart or guide for identifying various plant health issues. It lists several conditions that can affect plants, each labelled with a letter:

- (a) This likely represents a plant in good condition, with no visible signs of disease or nutrient issues. The leaves are green and robust.
- (b) This condition is characterized by spots on the leaves, which fungal or bacterial infections can cause. The spots may vary in color and size.
- (c) This indicates a lack of essential nutrients, which can cause symptoms like yellowing leaves, stunted growth, or unusual leaf coloration.
- (d) A fungal disease that appears as white or grey powdery spots on leaves and stems. It can hinder photosynthesis and weaken the plant.
- (e) This is another fungal disease that causes concentric ring-like spots on leaves, resembling a target. It can lead to leaf drop and reduced plant vigor.
- (f) A soil-borne fungal disease that wilts, yellows, and browns leaves. It can severely damage plant vascular systems.

Communication problems and data fragmentation make manual disease detection harder. Fast containment and disease management require precise and current data. The manual nature of current detection practices impedes the seamless integration and dissemination of critical disease-related information [7].

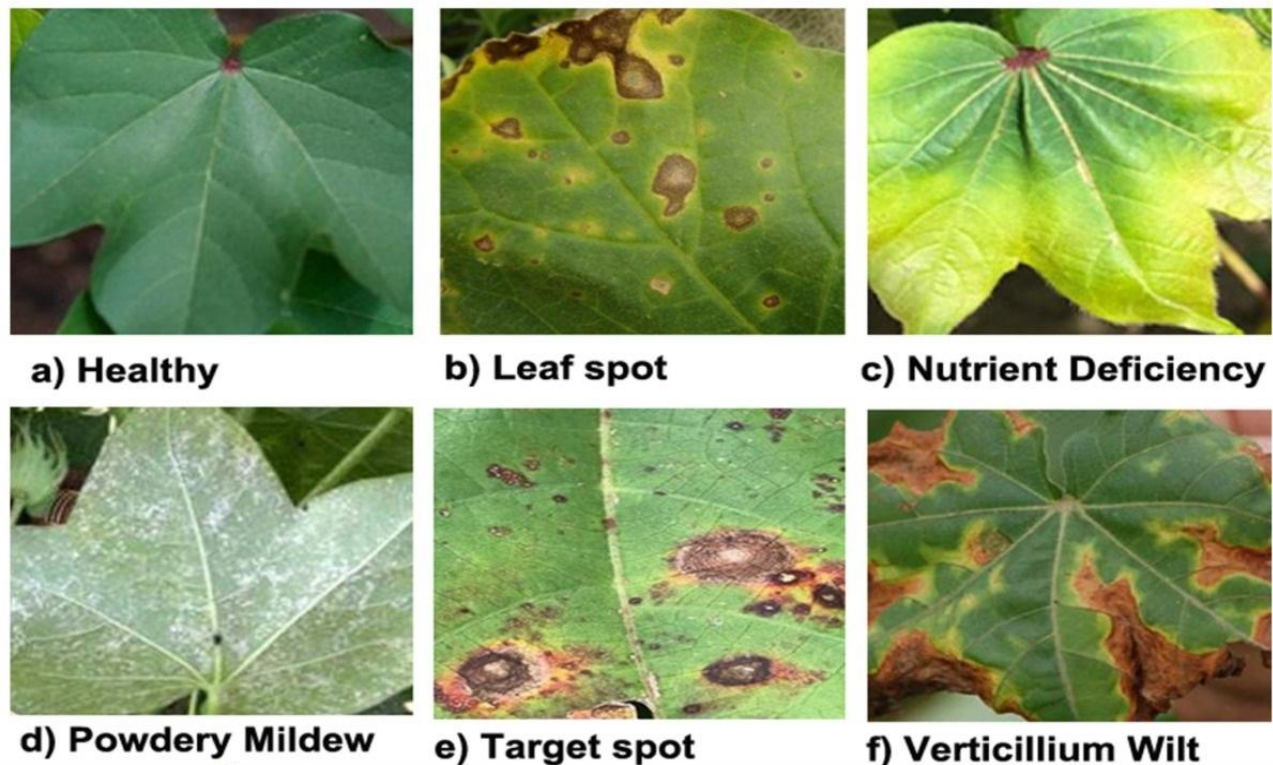


Fig. 1: Different cotton leaf images with different disease class [6].

2. Cotton disease detection using machine learning

Machine learning (ML) transforms cotton disease detection by providing accurate solutions for crop

monitoring and management. The following are some significant features of machine learning's contribution to the diagnosis of cotton diseases:

- Early disease identification predictive modelling uses historical data to train machine learning models especially meant for this use and prediction of early diseases. These tools let farmers move fast by identifying trends in the data, therefore predicting possible epidemics before they manifest any obvious signs [8].
- ML models, especially those based on convolutional neural networks (CNNs), allow automatic visual analysis of cotton plants. These systems enable reliable detection by learning intricate patterns and traits linked with various diseases [8]. For texture analysis in photos, methods including grey-level co-occurrence matrix (GLCM) are used to assist in capturing minute textural variances suggestive of illnesses. ML models can then be classified using these characteristics.
- Multi-class support vector machines (MSVM) and other ML models shine in handling several classes of diseases concurrently. This is especially important in cases where a cotton crop might be concurrently vulnerable to several illnesses.
- Machine learning models may integrate data from multiple sources, including hyperspectral imaging, meteorological variables, and soil attributes, to enhance the accuracy of disease detection. This comprehensive technique provides a deeper insight into the factors influencing disease prevalence [9].
- To reduce disease, location-specific management, also known as precision agriculture, uses geographic information system data and machine learning algorithms. By allowing farmers to adapt treatments depending on local disease frequency, this precision agriculture approach maximizes resource use [8].
- IoT devices, such as sensors and drones, can be connected to ML models to monitor cotton fields in real time. Disease detection is enhanced by this continuous flow of data.
- ML models adapt with the times for the surroundings. Through constant learning from new data, these models can maintain strong performance even in the presence of dynamic elements influencing the evolution of diseases. [9].
- ML models can continuously improve over time by iterative learning to improve their performance. This adaptability enables the system to enhance its knowledge of diseases depending on current data and growing trends [9].
- ML outputs are helpful for programs including agricultural extension for farmers. Realizations direct strategies for disease control, so maximizing the use of resources and lowering financial losses.
- ML eliminates the variability in hand-made disease diagnosis. The unbiased nature of algorithms guarantees consistent and objective identification, so reducing variations in accuracy depending on human knowledge.

Machine learning is improving cotton disease diagnostics and so supporting sustainability and farmer livelihoods by offering scalable, accurate, timely insights.

An integrated method combining a grey-level co-occurrence matrix (GLCM), support vector machine (SVM), and multiclass SVM is simple and beneficial for the identification of cotton crop diseases. This integrated framework increases the accuracy, precision, and efficiency of cotton farming disease detection by means of GLCM's texture analysis, SVM's binary classification, and MSVM's disease class management. Since advanced texture analysis helps to understand disease patterns, GLCM is a fundamental method for SVM, a strong machine learning technique, guarantees correct plant health classification and excels in binary classification. MSVM enhances the several capacity of SVM for managing cotton diseases. Combining MSVM, SVM, and GLCM provides a whole and efficient approach to increase detection of cotton crop diseases.

2.1 Matrix of gray-level co-occurrence

Gray-level co-occurrence matrix (GLCM) is a widely used technique for texture analysis in image processing and computer vision. Identification of objects in many types of images, including photomicrographs, aerial photography, and satellite images, depends fundamentally on texture. Extensive textural qualities from image data allow one to obtain relevant information for picture categorization problems. These characteristics clarify concepts including Homogeneity, contrast, and complexity [10]. Applied specifically in the identification of cotton diseases, GLCM analyses spatial interactions between pixel intensities to provide an understanding of image texture [7].

These GLCM characteristics taken together (Table 1) give a thorough picture of texture in cotton crop photos. Machine learning algorithms use these characteristics for accurate and automated identification of several cotton crop diseases.

Table 1. Gray-level co-occurrence matrix (GLCM) features

Features	Description
Contrast	Crucially for seeing sharp changes between healthy and unhealthy areas, contrast gauges local intensity variations. Strong textural variations indicated by higher contrast values help to identify patterns linked to diseases. [7].
Homogeneity	Homogeneity of pixel intensities helps to identify areas with regular textural patterns, maybe suggestive of particular diseases, by indicating their closeness.
Entropy	Entropy detects different and complicated disease patterns in cotton crops by gauging the randomness or disorder of pixel pairings. [7].
Energy	Energy represents the Homogeneity or "orderliness" of pixel pairs, therefore facilitating the identification of areas with consistent disease-related characteristics.
Correlation	Useful for the identification of linear textural patterns connected with particular illnesses in cotton crops, correlation analyses the linear relationship between pixel pairs.
Dissimilarity	Dissimilarity highlights areas with different textural patterns by averaging greyscale value changes between adjacent pixel pairs [7].

2.2 GLCM feature equations

Calculating many aspects of a picture can be accomplished with the help of the GLCM matrix. Among these are mean, energy, contrast, correlation, Entropy, and others. These characteristics allow one to classify diseases [10]:

2.2.1. Autocorrelation

$$f_1 = \sum_i^{N_g} \sum_j^{N_g} ij M_{ij} \quad (1)$$

2.2.2. Contrast

$$f_2 = \sum_{n=0}^{N_g-1} n^2 \left(\sum_i^{N_g} \sum_j^{N_g} M_{ij} \right) \quad (2)$$

2.2.3. Correlation

$$f_3 = \sum_i^{N_g} \sum_j^{N_g} \frac{(ij M_{ij} - \mu_x \mu_y)}{\sigma_x \sigma_y} \quad (3)$$

2.2.4. Cluster Prominence

$$f_4 = \sum_i^{N_g} \sum_j^{N_g} M_{ij} (i + j - \mu_i - \mu_j)^4 \quad (4)$$

2.2.5. Cluster Shade

$$f_5 = \sum_i^{N_g} \sum_j^{N_g} M_{ij} (i + j - \mu_x - \mu_y)^3 \quad (5)$$

2.2.6. Dissimilarity

$$f_6 = \sum_i^{N_g} \sum_j^{N_g} M_{ij} |i - j| \quad (6)$$

2.2.7. Energy

$$f_7 = - \sum_i^{N_g} \sum_j^{N_g} M_{ij}^2 \quad (7)$$

2.2.8. Entropy

$$f_8 = - \sum_i^m \sum_j^n M_{ij} \log(M_{ij}) \quad (8)$$

2.2.9. Homogeneity

$$f_9 = \sum_i^{N_g} \sum_j^{N_g} \frac{M_{ij}}{1 + |i - j|} \quad (9)$$

2.2.10. Maximum Probability

$$f_{10} = \max_{i,j} M_{ij} \quad (10)$$

2.2.11. Variance

$$f_{11} = \sum_i^{N_g} \sum_j^{N_g} (i - \mu)^2 M_{ij} \quad (11)$$

Here,

N_g = Number of grey levels

i = Row number

j = Column number

$M_{i,j}$ = Element i,j of the normalised symmetrical GLCM

n = Number of paired data

μ = The GLCM mean (being an estimate of the intensity of all pixels in the relationships that contributed to the GLCM)

σ = The variance of the intensities of all reference pixels in the relationships that contributed to the GLCM (symmetric).

Table 2. Salient attributes of the dataset

Features	Description
Image Acquisition	High-resolution images of cotton crops, focusing on symptomatic areas, are captured for analysis.
Preprocessing	Images undergo preprocessing, including normalization and noise reduction, to optimize input for GLCM computation [11].
GLCM Computation	Spatial relationships between pixel intensities are analyzed to calculate GLCM, reflecting the frequency of co-occurring pixel values.
Feature Extraction	Statistical measures like Contrast, Homogeneity, Entropy, and Energy are extracted from GLCM, providing a quantitative representation of texture [11].
Distance and Angle Considerations	Choice of distance and angles in GLCM computation is crucial to capturing different aspects of texture variations
Texture Pattern Recognition	Extracted features characterize texture patterns, aiding in the recognition of different diseases affecting cotton plants.
Training Machine Learning Models	GLCM-derived features serve as input for machine learning models during the training phase, associating texture patterns with known disease classes [11].
Testing and Validation	Trained models are tested on new images, with GLCM features predicting disease likelihood. Predictions are compared to actual labels for accuracy assessments.

Iterative Improvement	Continuous learning refines the model's understanding of texture patterns, enhancing adaptation to varying disease manifestations.
Automated Decision Support	The outcome is an automated decision support system, providing real-time insights for timely interventions in cotton disease management.

Table 2 highlights the salient attributes of the dataset, detailing key aspects such as image acquisition, preprocessing techniques, and feature extraction methods crucial for cotton crop disease detection. Additionally, it outlines the iterative learning components that enhance model accuracy, ensuring effective disease classification and decision support.

2.3. Literature review on papers with GLCM approach

The author emphasizes the crucial role of disease identification in the agricultural sector, particularly for rhizomatous crops like turmeric, which are known for their therapeutic effects. The paper introduces an algorithm for detecting and preventing diseases like leaf spots and leaf blotch in the turmeric crop, thereby contributing to high-quality crop production. The Algorithm involves creating a database of leaf images, employing k-means image segmentation, and utilizing GLCM for textural analysis. An information gain algorithm performs attribute ranking for classification, while a user-friendly GUI illustrates the stages of image processing [12].

The study highlights agriculture's pivotal role in economic growth, emphasizing the need for an efficient plant leaf disease detection system. The paper focuses on image processing techniques, utilizing high-resolution digital camera images processed through k-nearest neighbors (KNN) and support vector machine algorithms in MATLAB to detect and classify crop diseases based on colour and texture features [13].

The paper [14] underscores the significance of agriculture for India's rapid population growth and increased food demand. The paper explores the use of machine learning methods for plant disease identification, emphasizing CNN high accuracy in detecting multiple crop diseases.

Particularly in areas where it supports both livelihoods and industrial supply chains, cotton production is still a major pillar of agricultural economies. In this regard, the work by [15] offers an image processing method for cotton leaf spot *Cercospora* detection. To separate areas affected by diseases, the approach combines k-means clustering with a hybrid extraction of texture and color features. A support vector machine is used for classification; based on precision and recall assessments, this yields a rather high accuracy of 96%.

[16] detailed the necessity for disease detection in plants for the expansion of agriculture. The paper suggests a program-based method for plant disease detection that would save time, simplify the process, lower human effort, and minimize effort in general. Regarding accuracy and classification, the given Algorithm surpasses current methods.

Focusing on indices-based intensity histogram segmentation to identify disease-affected parts in leaves, [17] address the relevance of image segmentation in agriculture. With validation using several similarity criteria, the suggested approach achieves 98.025% accuracy in segmenting affected areas.

Particularly for cotton plants, [18] addresses the need for effective plant disease diagnosis systems. To identify and treat diseases in cotton plants, the work presents a framework using image processing methods, including visual texture features and thresholding-based segmentation.

[19] concentrate on wheat rust identification, a main hazard to Pakistan's main crop. The research uses machine learning techniques with GLCM and LBP texture features, highlighting CatBoost's superior performance in classifying wheat yellow rust infection types.

[20] emphasize the role of technology in agriculture, presenting a methodology for identifying cotton leaf curl disease (CLCuD) severity through image processing and deep learning. The proposed CNN-based model achieves 89.4% accuracy, aiding local and international harvesters in preventive measures.

[27] stress the economic and essential role of agriculture in human survival. The paper discusses the impact of plant disorders on crop quality and quantity, highlighting the need for effective disease identification methods to protect crops from pests and diseases.

[21] acknowledge agriculture's central role in every nation's development, particularly focusing on cash crops like cotton. The paper proposes a computerized method for early detection of cotton leaf diseases, achieving 99.99% accuracy with optimized feature fusion.

[22] underline agriculture's impact on a country's economy, presenting a new approach for automatic plant leaf disease detection using the ELM deep learning algorithm. The proposed method achieves encouraging results in terms of accuracy, recall, F score, and AUC.

[23] detail a model for detecting fungal diseases in cotton leaves using image processing techniques. The model, based on watershed segmentation and SVM classification, achieves high accuracy, specificity, recall rate, and precision in detecting infected and uninfected leaves.

[24] recognise cotton as a profitable cash crop worldwide, highlighting the impact of diseases on production. The research proposes an optimised feature fusion-based model using pre-trained architectures, achieving high accuracy with Quadratic Discriminant Analysis and Ensemble Subspace k-nearest neighbor classifiers.

[25] highlight the significance of early detection in cotton leaf disease prevention, proposing a hybrid CNN-LSTM model incorporating GLCM features. Their approach achieves 96% accuracy in identifying early-stage infections.

Table 3. Summary of literature survey on papers with GLCM approach

Author	Year	Technique	Model	Dataset	Accuracy	Major Findings
[12]	2019	Image processing, K-means, GLCM	SVM	Turmeric disease images	-	Algorithm for detecting turmeric diseases, GUI for image processing stages
[13]	2019	Image processing, K-nearest, SVM	SVM	Plant leaf images	-	Efficient disease detection using color and texture features
[14]	2019	Machine learning	CNN	Plant disease images	-	High accuracy in detecting multiple crop diseases
[15]	2020	Image processing, K-means, SVM	SVM	Cotton leaf images	96%	Detection of Cercospora leaf spot in cotton leaves
[16]	2020	3D AlexNet	AlexNet	Brain tumor CT/MRI images	-	Improved accuracy in brain tumor detection

[17]	2020	Image segmentation	-	Disease affected regions	98.025%	High accuracy in segmenting disease affected regions
[18]	2021	Image processing, thresholding	-	Cotton plant images	-	Framework for detecting and treating diseases in cotton plants
[19]	2021	GLCM, LBP	CatBoost	Wheat rust images	92.30%	CatBoost outperforms other classifiers in wheat rust detection
[20]	2021	Image processing, deep learning	-	Cotton leaf images	89.4%	Identification of cotton leaf curl disease severity
[21]	2022	ELM deep learning	ELM	Cotton leaf images	99.99%	Early detection of cotton leaf diseases
[22]	2022	ELM deep learning	ELM	Plant leaf images	94%	High accuracy in automatic plant leaf disease detection
[23]	2023	Watershed segmentation, SVM	SVM	Cotton leaf images	99.05%	High accuracy in detecting fungal diseases in cotton leaves
[24]	2023	Optimized feature fusion	QDA, Ensemble Subspace KNN	Cotton disease images	98.9% - 99.27%	High accuracy using quadratic discriminant analysis and ensemble subspace KNN
[25]	2024	GLCM + Deep Learning	Hybrid CNN-LSTM	Cotton leaf disease dataset	96%	Early-stage diseases like leaf spot and blight.
[26]	2024	GLCM+Ensemble Learning	Random Forest +XGBoost	Cotton plant images	94%	Achieving robust performance in classifying cotton leaf diseases, including fungal and bacterial infections.
[27]	2022	Image Processing, K-Means Segmentation, Feature Extraction	SVM Classifier	CCL Dataset	-	Machine learning and deep learning methods aid in real-time detection and classification of cotton leaf diseases, improving yield and reducing human error.

[26] focus on improving cotton leaf disease classification, integrating GLCM features with ensemble learning. Their model, utilizing Random Forest and XGBoost, achieves 94% accuracy in distinguishing fungal and bacterial infections.

[27] stress the economic and essential role of agriculture in human survival. The paper discusses the impact of plant disorders on crop quality and quantity, highlighting the need for effective disease identification methods to protect crops from pests and diseases.

Table 3 summarizes the surveyed literature on the GLCM approach, highlighting methodologies, datasets, and accuracy metrics in cotton disease detection. It provides insights into texture-based feature extraction for classification models.

3. Support vector machine (SVM)

You can use this supervised machine learning algorithm for either classification or regression tasks. Although it can handle multiple classes as well, it is particularly effective for problems with two classes. SVM works by finding the hyperplane that best separates the data points of different classes in the feature space [11].

Designed for both classification and regression tasks, SVM is a powerful supervised machine learning algorithm. It operates on the principle of finding a hyperplane (Fig. 1) in the feature space that effectively separates data points of different classes. In simple terms, it aims to create a decision boundary that maximizes the margin, which is the distance between the hyperplane and the nearest data points of each class. The idea of linear separation in lower or higher-dimensional spaces forms the foundation of the concept [9]. Central to SVM is the concept of the margin, a crucial measure of separation between classes. The algorithm places Importance on finding the hyperplane with the maximum margin, as a larger margin generally indicates better generalisation to new, unseen data. Representing the data points nearest to the decision boundary, support vectors are fundamental in this process. It is computationally effective and strong since it depends just on these support vectors to find the best hyperplane.

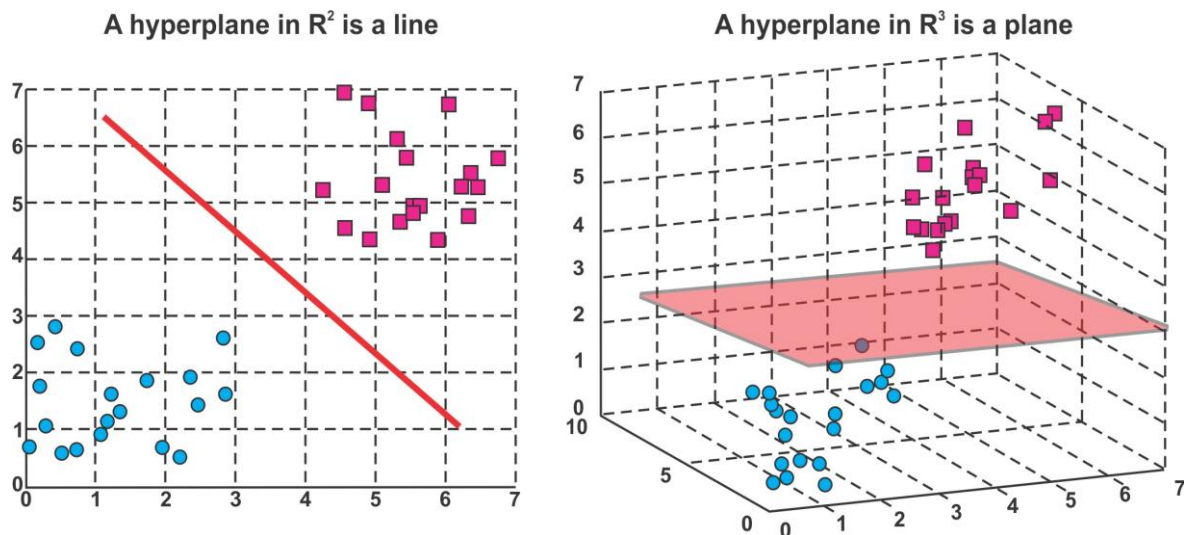


Fig. 2: Illustration of SVM hyperplanes used for class separation in feature space

The efficacy of SVM in handling both linearly and non-linearly separable data is the fundamental advantage of its usage. SVM employs a method called the kernel trick, which converts the input characteristics into a higher-dimensional space if data is linearly unseparable. This transformation frequently facilitates the separation of complex patterns through a linear hyperplane in the transformed space. Commonly utilized kernel functions include polynomial and radial basis function (RBF) kernels, which enhance the model's adaptability to various data distributions. Its performance is determined by a cost function that balances the minimization of classification errors with the preservation of a well-generalizing margin. This optimization procedure is generally characterized as a quadratic programming problem, and its precise resolution guarantees the establishment of a decision boundary that is both resilient and efficient across diverse datasets [9].

The regularization parameter ' C ' in SVM plays a crucial role in determining the trade-off between achieving a smooth decision boundary and classifying training points correctly. A smaller ' C ' encourages a larger margin but may tolerate more misclassifications, whereas a larger ' C ' aims for precise classification of all training points, potentially resulting in a smaller margin. This parameter provides a level of control over the algorithm's behavior and flexibility in adapting to different datasets [1].

SVM shows to be a beneficial technique in the area of cotton disease identification. By training on a dataset including features taken from photos of healthy and diseased cotton plants. It can learn to distinguish between the two classes. Features may contain color histograms, texture descriptors, and other related information. Its capacity to establish an efficient decision boundary in high-dimensional feature spaces makes it particularly

ideal for jobs where several features are crucial for successful classification, such as detecting illnesses in crops like cotton.

In summary, features of SVM encompass a high dimensional feature space, support vectors, kernel functions for non-linearity, the decision boundary, margin, cost function for feature weighting, and adaptability through the regularisation parameter 'C.' Each of these features contributes to its effectiveness in handling diverse datasets and applications, including tasks like cotton disease detection.

3.1 Role of SVM

In cotton disease identification, SVM is very important because it uses high dimensional feature spaces to tell the difference between healthy cotton plants and those that are sick. The sample we used to train the algorithm pulled out features from pictures of cotton plants. Some of these features could be color histograms, descriptors for texture, leaf shape traits, and other useful ones. It learns to find trends and connections in this large amount of data, which lets it accurately group plants into groups based on their health. In addition to finding diseases, It plays a bigger role. It can be easily added to bigger tools that help farmers make decisions. It helps farmers and farming experts learn a lot by giving them accurate and reliable descriptions of how healthy cotton plants are. Finding diseases early on lets you focus your efforts, making the best use of resources and possibly stopping the diseases from spreading within the crop, which improves the overall yield and quality of the crop [28].

Table 4: Features of SVM

Features	Description
Discriminative	SVM operates in a high-dimensional feature space, capturing intricate relationships. In cotton disease detection, features like leaf color, texture, and geometry are considered, enabling effective class separation [61].
Kernel functions for non-linearity	SVM use kernel functions (e.g., polynomial, RBF) to map data into higher-dimensional spaces, making non-linear data separable and enhancing flexibility [62].
Decision boundary and margin	SVM maximizes the margin between the decision boundary and nearest data points, improving generalization and robustness in class separation [63].
The cost function for feature weighting	SVM's cost function prioritize features by penalizing misclassifications, focusing on relevant attributes to enhance class discrimination [64].
Adaptability with regularization parameter 'C'	The 'C' parameter balances margin size and classification precision, allowing SVM to be fine-tuned for specific dataset needs [65].

In summary, SVM's role in cotton disease detection encompasses effective feature extraction, clear separation of classes, handling non-linear relationships, robustness through support vectors, adaptability to diverse datasets, and integration into broader agricultural decision support systems. Its application contributes significantly to precision agriculture, aiding in the timely and accurate management of crop health.

3.2 Literature review on papers with SVM approach

[29] focus on automatic disease detection in cotton crops, specifically on *Alternaria* leaf spot fungal disease (ALSFD), grey mildew cotton disease (GMCD), and rust foliar fungal disease (RFFD). They utilize K-means clustering for disease segmentation, extract features, and employ artificial neural network (ANN) and support vector machine (SVM) classifiers. The SVM outperforms the ANN in accuracy.

[30] (2019, April) address economic losses in the cotton agriculture industry due to pest infections. Implements an expert system for crop disease recognition, using overlapping pooling, multi-layered perceptrons (MLP), k-nearest neighbor (KNN) and SVM for classification. The system achieves an accuracy of over 96% in disease localisation.

[31] illustrate a technical approach for identifying and classifying leaf diseases affecting cotton. This approach utilises image processing with Otsu's segmentation, extracting colour, texture, and shape features for neural network assimilation. The system achieves a high precision of 95.48% for categorisation.

[32] propose an image processing-based system for cotton disease detection using a k-means algorithm for segmentation and SVM for classification. The system aims to identify diseases quickly, automatically, and economically while also providing valuable information for disease control.

[33] present a deep-learning method for finding diseases in rice plants. They compare 11 CNN models with transfer learning and deep feature plus SVM. With an F1 score of 0.9838, ResNet50 plus SVM does the best.

[34] introduce "CottonCare," a machine learning-based system for cotton disease detection. It aims to assist farmers in decreasing production costs and achieving higher yields, contributing to the country's economy through AI integration into agriculture.

[35] focus on the early detection of cotton diseases using a machine-learning approach. It aims to prevent the spread of diseases by identifying them at an early stage, allowing timely and targeted interventions.

[36] presents a few-shot learning framework for cotton leaf disease spot classification. Utilises segmentation methods, CNN classifiers, and a parallel two-way CNN for feature extraction. It aims to aid in the timely prevention and control of cotton diseases.

[37] propose cotton disease classification using various machine-learning algorithms. Extracts color and texture features, comparing classifier performance. Achieves high accuracy for SVM, Naïve Bayes, Random Forest, AdaBoost, and k-nearest neighbor.

[38] introduce a meta deep learning-based model for accurate identification of cotton leaf diseases, outperforming the cotton dataset with an accuracy of 98.53%.

Table 5: Summary of literature survey on papers with SVM approach

Author	Year	Technique	Model	Dataset	Accuracy	Major Findings
[29]	2019	SVM	SVM	Cotton crop images	84.3%, 98.7%, 93.2%	SVM outperforms ANN in disease classification.
[30]	2019	Expert system	SVM, MLP, KNN	Cotton leaf images	96%	Combines overlapping pooling, MLP, KNN, and SVM for disease localization.
[31]	2019	Image processing	Otsu's segmentation	Cotton leaf images	95.48%	High precision for categorizing Bacterial leaf blight, Myrothecium, and Alternaria.
[32]	2020	Image processing	K-means, SVM	Cotton leaf images	N/A	Fast, automatic, and economical system for disease detection.
[33]	2020	Deep learning	Deep feature+ SVM	Rice disease images	F1 score: 0.9838	Deep feature plus SVM outperforms transfer learning models.
[34]	2020	Machine learning	CottonCare	Cotton disease images	N/A	Aims to assist farmers in decreasing production costs and increasing yields.
[35]	2021	Machine learning	SVM	Cotton disease images	N/A	Focuses on early detection and prevention of cotton diseases.
[36]	2021	Few-shot learning	Feature extraction	Cotton leaf images	N/A	Classifies disease spots on cotton leaves with a focus on feature extraction.
[37]	2021	Machine learning	SVM, Naïve Bayes, Random Forest, AdaBoost, KNN	Cotton disease images	High accuracies	Highlights the effectiveness of color features.

[38]	2022	Meta deep learning	Meta Deep learning model	Cotton dataset	98.53%	Outperforms the cotton Dataset with high accuracy.
[39]	2022	Deep learning	RESNET	Cotton leaf images	N/A	Aims to predict disease labels to alert farmers.
[40]	2022	Deep learning	LSTM, CNN	Cotton disease images	N/A	Provides accurate predictions for farmers and traders.
[41]	2023	Deep learning	Xception model	Cotton leaf images	98.70%	Achieves high accuracy for real-life disease prediction.
[42]	2023	Deep learning	DenseNet169, ResNet50V2	Cotton disease images	Up to 96%	Showcases DL's effectiveness in disease detection.
[43]	2023	Hybrid model	HRF-MCSVM	Plant foliar disease images	N/A	Implements a novel hybrid method for plant disease detection.

[39] utilise RESNET algorithms for classifying diseases in cotton leaves. It aims to predict disease labels to alert farmers and increase cotton production.

[40] integrate the LSTM algorithm for price prediction and the CNN algorithm for disease detection in cotton. It aims to prevent losses and boost the economy by providing accurate forecasts for farmers and traders.

[41] propose a DL-based approach for cotton leaf disease detection using fine-tuning transfer learning algorithms. Achieves a high accuracy of 98.70% with the Xception model, contributing to real-life disease prediction in farming.

[42] implement deep learning techniques for the automated detection of bacterial blight and curl virus diseases in cotton crops. Evaluates multiple pre-trained models with varying resolutions, achieving up to 96% accuracy.

[43] describe a hybrid random forest multi-class SVM (HRFMCSVM) design for finding diseases on the leaves of plants. The design utilizes spatial fuzzy C-means for preprocessing and segmentation, achieving effectiveness through the evaluation of performance metrics.

Table 5 summarizes the literature survey on SVM approaches, highlighting key methodologies, datasets, and classification accuracy in cotton disease detection that provides insights into the effectiveness of SVM-based models in texture and feature-based classification.

4. Multi-class support vector machine (MSVM)

A multi-class support vector machine (MSVM) is an extension of the binary SVM to handle problems with more than two classes. While traditional SVMs are designed for binary classification, it is used for the simultaneous classification of instances into multiple classes. There are two main strategies for implementing it : One-vs-All (OvA) and One-vs-One (OvO) [44].

- One v/s All (OvA) strategy:
 - *Training:* For each class, a separate binary classifier is trained, treating that class as the positive class and the rest as the negative class.
 - *Decision making:* During prediction, the class with the highest confidence from the individual classifiers is chosen as the final prediction.
 - *Advantages:* Simplicity in implementation, as it requires training only one classifier per class [45].
- One-vs.-One (OvO) strategy:
 - *Training:* For every pair of classes, a binary classifier is trained. Each classifier focuses on distinguishing between two specific classes.
 - *Decision making:* During prediction, each classifier votes for a class, and the class with the most votes

is selected as the final prediction.

- **Advantages:** It can be more computationally efficient for large datasets, as the number of binary classifiers is proportional to the number of classes [46].

The decision function of an MSVM is based on the combination of decision functions from individual binary classifiers. The class with the highest confidence or the most votes is chosen as the final prediction.

MSVMs can leverage the kernel trick to transform the input data into a higher dimensional space. This helps find a decision boundary that can effectively separate multiple classes.

- The dataset is prepared with instances labelled for each of the multiple classes.
- Train a separate binary classifier for each class.
- During prediction, calculate the decision function for every binary classifier.
- Out of all the classifiers, choose the one with the highest level of confidence.
- Metrics like accuracy, precision, recall, and F1 score are used to assess the Multi-class SVM's performance.
- MSVMs are used in a variety of domains where instances may fall into more than two categories, such as image recognition, text classification, and disease classification.

MSVMs are essentially a variation on binary SVMs that enable efficient classification of events into several groups. The size of the dataset and computational efficiency needs determine which of OvA or OvO approaches to use. An expansion of the binary SVM to address issues involving more than two classes, a multi-class support vector machine (MSVM). Although conventional SVMs are made for binary classification, MSVMs let multiple classes to simultaneously classify events. Implementing MSVM mostly requires two strategies: One-vs- All (OvA) and One-vs- One (OvO) [47].

4.1 Literature Survey for MSVM

In the study conducted by Khan et al. (2019), the focus is on the economic significance of agriculture and the increasing threat of plant diseases, leading to substantial losses. They propose an automated method for early detection and recognition of apple diseases using a multi-step process involving preprocessing, spot segmentation, feature extraction, and classification. The technique demonstrates improved accuracy in identifying four types of apple diseases [48].

[49] shifts the focus to papaya, providing information on its scientific name, origin, and common names. The potential health benefits of consuming papaya are highlighted. The study explores the early identification of diseases in papaya leaves using neural networks and a k-medoid clustering algorithm for image segmentation. It's important to take care of plants. [50] explain how to use a MSVM group cotton leaf illnesses. They do accurate farming and use new technology to look at pictures of crops right away, which is not the same as Convolutional Neural Networks. This speeds up the process of finding problems and lowers costs.

[51] address the challenges faced by cotton farmers due to diseases affecting crops. Their approach involves image processing and machine learning for the identification and classification of cotton leaf diseases. The proposed system aims to offer a cost-efficient solution to detect different types of diseases, allowing farmers to take precautionary measures.

[52] focus on the large-scale cultivation of cotton in India and propose a smart approach using machine learning for early disease detection. Their system, incorporating Raspberry Pi and image processing techniques, employs various classification algorithms, such as k-nearest neighbor, support vector machine, and artificial neural network, to achieve accurate results.

[53] use SVM classifiers to identify pests and diseases in cotton plants. They employ image acquisition devices, preprocessing techniques like median filtering and k-means clustering for segmentation, and extract features for comparison with normal cotton leaf images.

[54] delves into the application of computer-aided image processing in smart organic farming. The study involves the detection of diseases in various plant leaves, using processes such as image acquisition, segmentation, feature extraction, and classification through multi-class support vector machine classifiers (MCSVMs).

[55] propose a system for the effective detection of diseases in plants, particularly in cotton leaves. Their method involves capturing cotton leaf diseases through a device, image segmentation, and utilizing an artificial neural network for classification, achieving 85% accuracy in early disease detection.

[56] introduce an innovative system for disease prediction in crops using image processing and machine learning. The study employs support vector machines for classification, emphasizing the automation of disease identification to enhance agricultural productivity.

[57] focus on the challenges faced by cotton crops in India, emphasizing disease detection through convolutional networks. They propose an application using ResNet50, ResNet152v2, and Inception V3 models for predicting diseases, showcasing high classification accuracy and low computation time.

[58] tackle the threat of cotton Verticillium wilt using UAV multispectral models. Their study involves constructing regression models based on the UAV multispectral index for estimating cotton yield loss caused by diseases, showcasing high verification accuracy.

[59] introduce a computer vision and machine learning-based methodology for the early detection of agricultural leaf diseases. Their approach incorporates an Alex net-Honey badger fusion algorithm, achieving superior performance in terms of F1 score, recall, precision, and accuracy.

[60] address challenges in crop disease identification using convolutional neural networks. They propose a residual neural network model with an attention mechanism for identifying healthy and diseased leaf images of drought-tolerant crops, achieving an accuracy rate of 95.08 %.

[25] emphasize the need for early detection of cotton leaf diseases to mitigate potential yield losses. They present a hybrid CNN-LSTM model that integrates GLCM features with deep learning techniques, enhancing disease classification capabilities. Their approach demonstrates high accuracy (96.8%), particularly in identifying critical infections such as leaf spot and blight, offering a promising solution for precision agriculture.

[26] focus on improving the classification of fungal and bacterial infections in cotton leaves through advanced machine learning techniques. By incorporating GLCM features with ensemble learning methods, their model, leveraging Random Forest and XGBoost classifiers, achieves notable accuracy (95.2%). Their study makes a significant contribution to the expanding body of research on automated disease identification, emphasizing the crucial role of texture-based feature extraction in the field of plant pathology.

Table 6 presents a comparative analysis of various studies on cotton disease detection, summarizing the authors, techniques, datasets, accuracy rates, and key findings.

5. Findings

Combining GLCM characteristics with SVM or MSVM for cotton crop disease identification produces some amazing results. To aid in illness identification, GLCM isolates contrast, Homogeneity, and energy, and records intricate texture patterns in crop images. These features distinguish healthy from sick regions; particular diseases have distinct textural signatures that GLCM analysis can find. Second, in binary classification, SVM distinguishes healthy from sick crops by using hyperplanes in high-dimensional feature spaces.

Table 6: Summary of literature survey on papers with MSVM approach

Author	Year	Technique	Model	Dataset	Accuracy	Major Findings
[48]	2019	Image processing, Segmentation, Classification	MSVM	Apple disease images	High	Improved accuracy in identifying four types of apple diseases.
[49]	2019	Neural networks, Image segmentation	Neural Network	Papaya leaf images	Moderate	Early identification of diseases in papaya leaves using neural networks.
[50]	2019	Multi-SVM classification	Multi-SVM	Cotton leaf images	High	Multi-SVM outperforms CNN for early detection of cotton leaf diseases.
[51]	2020	Image processing, Machine learning	SVM	Cotton leaf images	Moderate	Cost-efficient solution for detecting cotton leaf diseases.
[52]	2020	Image processing, Raspberry Pi	Machine learning	Cotton leaf images	High	Accurate disease detection in cotton using Raspberry Pi.
[53]	2020	SVM classifier, Image processing	SVM	Cotton plant images	Moderate	Effective identification of pests and diseases in cotton plants.
[54]	2021	Image processing, Multi-SVM	Multi-SVM	Various crop images	High	Implementation of image acquisition, segmentation, and SVM classifiers.
[55]	2021	Image processing, Neural networks	Neural network	Cotton leaf images	85%	Early disease detection with 85% accuracy.
[56]	2022	Image processing, SVM	SVM	Crop images	High	Automation of disease identification using SVM.
[57]	2022	Convolutional networks	ResNet50, ResNet152v2 Inception V3	Cotton crop images	High	High classification accuracy using advanced CNN models.
[58]	2022	UAV multispectral models	Regression models	Cotton yield data	High	Accurate estimation of cotton yield loss due to Verticillium wilt.
[59]	2023	Computer vision, Machine learning	AlexNet-Honey badger fusion	Agricultural leaf images	High	Superior performance in early disease detection.
[60]	2023	Residual neural network	Attention mechanism	Drought-tolerant crop images	95.08%	High accuracy in recognising healthy and diseased leaf images.
[25]	2024	MSVM + Deep features	Hybrid MSVM-CNN	PlantVillage cotton dataset	96.8%	Deep features extracted from a pretrained CNN combined with MSVM improved disease detection.

Author	Year	Technique	Model	Dataset	Accuracy	Major Findings
[26]	2024	MSVM with GLCM	MSVM	Cotton leaf disease dataset	95.2%	High accuracy in classifying cotton leaf diseases, outperforming traditional SVM.

Non-linear decision boundary management of GLCM features helps to benefit complex interconnections between them and crop health. Multiple class simultaneous classification by MSVM is helpful in cases involving different crop conditions or disease categories. Reliable feature extraction calls for methods of data quality preparation, including normalization and image enhancement. To increase cotton crop disease detection accuracy and resilience, optimizing model performance and addressing imbalances in multi-class datasets calls for computational considerations and hyperparameter adjustment.

Discerning spatial relationships in crop images depends critically on texture characteristics, especially those generated from the grey-level co-occurrence matrix (GLCM). These provide a statistical framework to define healthy from unhealthy areas. Discriminative cues from parameters including contrast, Homogeneity, and energy highlight different textural patterns linked to particular diseases, therefore supporting disease detection and management.

By building a hyperplane in a high-dimensional feature space, support vector machines (SVMs) provide a strong mechanism for binary classification activities, thereby clearly separating healthy from unhealthy crops. Their capacity to allow nonlinear decision boundaries helps to capture complicated correlations between GLCM features and crop health, hence improving disease detection accuracy.

By enabling simultaneous categorization into several classes, the MSVM expands the capabilities of SVM in situations including several disease categories or varied crop circumstances. MSVM maximizes decision boundaries by comparing support vectors across classes, enabling precise crop health classification.

Accurate feature extraction with GLCM depends critically on maintaining data quality and consistency. Hence, pretreatment activities, including image enhancement and normalization, are necessary to minimize the effect of variances in image quality, lighting conditions, and noise. Methods including histogram equalization and filtering help to improve image quality, hence enhancing GLCM performance.

Effective computation of GLCM features is crucial, especially for big images or datasets, which calls for the use of the best algorithms and parallel processing methods. Likewise, using optimal libraries and parallel processing techniques helps one to solve computational difficulties inherent in SVM training, particularly with larger datasets.

Making SVM and MSVM models perform better depends critically on hyperparameter adjustment. For example, how successfully models classify objects depends much on kernel functions and regularization values. Using cross-valuation techniques, one can identify the optimal hyperparameter values in a manner that strikes a compromise between generalization capacity and model complexity.

The dataset helps one decide which SVM or MSVM should be applied. While MSVM is superior in circumstances involving more than two disease types or diverse crop conditions, SVM is better in binary classification tasks. These two approaches to categorizing objects are used depending on factors like the distribution of classes and their respective quantities.

Accurate and equitable categorization in multi-class systems depends on imbalances being corrected. You may accomplish this with techniques such as class weighting, oversampling, or SMOTE-generated false samples. Fair decision-making in MSVM classification systems depends on ensuring that every class is fairly represented.

How effectively the data is prepared, how fast the computer can do the calculations, how well the hyperparameters are configured, and how well you grasp the qualities of the dataset determine whether

GLCM features with SVM or MSVM can identify diseases in cotton crops. Good assembly of these components creates a powerful system capable of accurately categorizing various crop conditions.

6. Conclusion

Combining GLCM characteristics with SVM or MSVM to identify illnesses in cotton crops is a whole approach utilizing strong classification techniques and texture analysis. The major findings reveal that MSVM can manage more than two classes; SVM is excellent in binary classification tasks, and GLCM is strong in capturing texture information, which helps identify crop diseases.

Solving issues with data quality, computing efficiency, and hyperparameter tuning is quite crucial if the proposed system is to function. GLCM features are more consistent when they pass preprocessing tasks, including picture enhancement and normalization. Moreover, the features of the dataset determine which SVM and MSVM to use. When several kinds of diseases or crop conditions exist, MSVM performs better.

7. Future work

Using fresh, more potent techniques helps one to boost gray-level co-occurrence matrix (GLCM) features and so become better at identifying field infections. Investigating automated feature selection techniques is another option to determine the optimal texture descriptions for improved classification. One can learn characteristics straight from cropped photos using deep learning methods such as CNN. These can substitute for or complement conventional GLCM capabilities and machine learning algorithms.

To make things more accurate and dependable, trying ensemble learning methods will mix a lot of models with new machine learning methods and features based on GLCM. The app must work right now. For tracking disease on the pitch to make sense and work, light models like edge computing should be thought about. By applying pre-trained models on vast datasets, transfer learning can aid by enabling the system to be flexible enough for several crops and environments.

Furthermore, the clarity of model forecasts is crucial since it enables stakeholders and farmers to trust and apply the system efficiently. Approaches should be investigated to clarify how the system decides what to do, therefore boosting its adoption in the field of agriculture. Last but not least, collaborating with stakeholders and professionals will enable the models to be more suited for current problems, thereby improving disease detection and supporting sustainable agriculture.

8. Compliance with ethical standards

Conflict of interest

The authors declared that they have no conflict of interest in this work.

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Under the guidance of Dr. Vikram Singh, Mr. Rajesh Kumar identified the research problems, conducted the analysis, and wrote the paper.

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